

# Maximum Flows and Parametric Shortest Paths in Planar Graphs [3]

Filip Koprivec

Faculty of Mathematics and Physics, IMFM

June 2020

# Maximum flow problem

Given a

- Directed graph  $(V, E)$  (simple)
- Edge capacities (weights):  $c : E \rightarrow \mathbb{R}^+$  (maximum available edge flow)

and  $s, t \in V$

Find a feasible flow  $f : E \rightarrow \mathbb{R}^+$

- $f(e) \leq c(e)$  Satisfies capacity constraints
- Conserves flow:

$$\forall v \notin \{s, t\}. \sum_{u \rightarrow v} f(u \rightarrow v) = \sum_{v \rightarrow w} f(v \rightarrow w)$$

Find one with

$$\max\left(\sum_{s \rightarrow v} f(s \rightarrow v)\right)$$

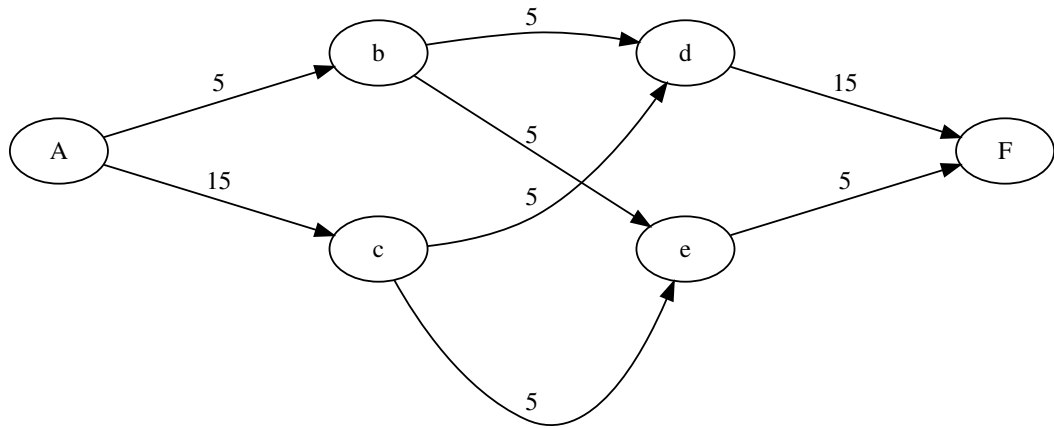


Figure: Input graph

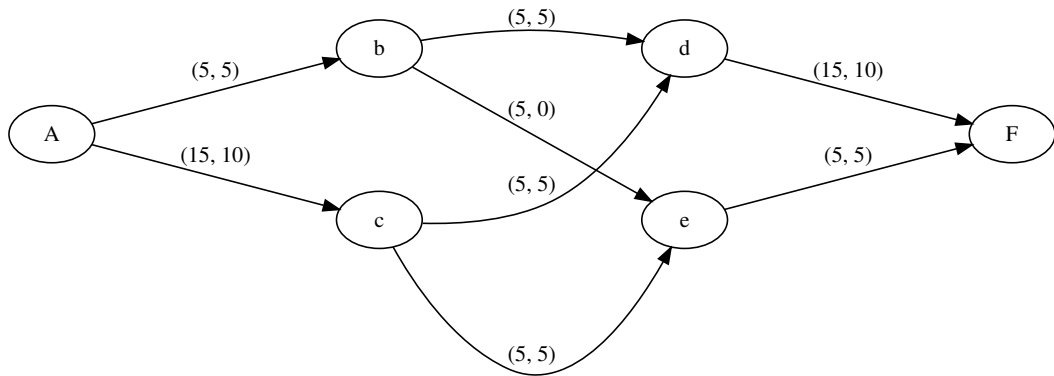


Figure: Possible solution: 15

## Direct practical applications

- Max flow (routing problems)
- Huge impact in data centers
- Various aspects of resource management and scheduling ("baseball elimination" problem, project resource allocation)

First studied by Soviets before WW2, used by USA military planners during the cold war to assess military capabilities [6].

The solution for East European railway (10 stations, ~70 connections) was produced by hand.

- Classical Ford-Fulkerson algorithm [4] ( $O(Ef)$ ) and Edmonds-Karp ( $O(VE)$ ), Dinic ( $O(VE \log E)$  using dynamic trees).
- Max-flow min-cut theorem (Max-flow and min-cut are a reformulation as a primal-dual linear programs)

Most direct applications of maximum flow problems can be modeled as planar graphs, so the question is, whether better solutions exist in such cases.

- Computing flow with a fixed value is equivalent to computing a SSSP in a particular dual Graph  $G^*$  [5].
- In 2009 An  $O(n \log n)$  algorithm was described for arbitrary directed planar graphs [1] (using clockwise/counterclockwise cycling to saturate network).
- Problem is intricately connected to the shortest paths in dual graph  $\rightarrow$  most of the solutions rely on fast SSSP algorithms
- SSSP can be computed in linear time (with no negative weights), when  $s$  and  $t$  are on the same face, the problem is linear.

A simpler derivation of  $O(n \log n)$  algorithm [1]

- Reformulate max-flow as a parametric SSSP in dual graph
- Solve SSSP in the dual
- Devise an upper bound of number of changes in the dual
- Construct a higher genus graph, that achieves upper bound



# Dual graph

WLOG: Assume that all edges have a reverse pair

$$(u \rightarrow v)^* := u^* \uparrow v^*$$

$$u^* \uparrow v^* := (u \rightarrow v)^*$$

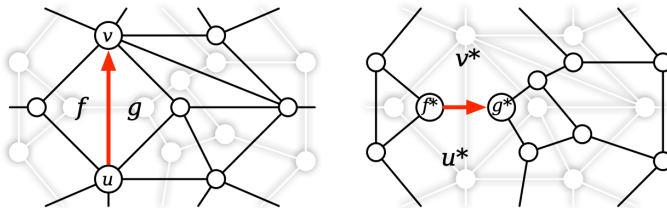


Figure: Dual graph [3]

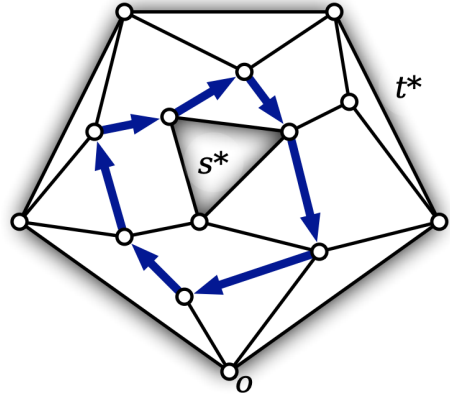
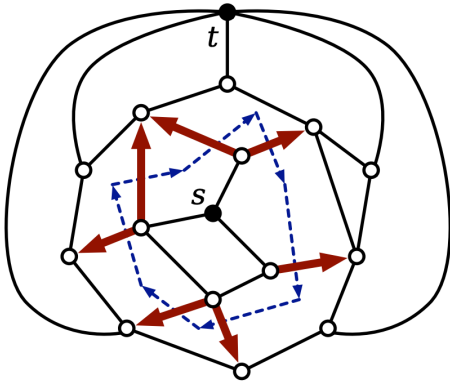
$$\begin{aligned}\phi : E &\rightarrow \mathbb{R} & \phi(e) &= 0, e \notin E \\ \phi(e) &= -\phi(\text{rev}(e)) & \sum_w \phi(v \rightarrow w) &= 0\end{aligned}$$

Feasible if  $\phi(e) \leq c(e)$ . Flow saturates an edge if  $c(e) = \phi(e)$ . For a cut  $C \subseteq E$ :  
 $\phi(C) = \sum_{e \in C} \phi(e)$ .

By the max-flow min cut, if  $C$  is saturated, then  $\phi(C)$  is max flow.

# Reformulation

Cut is called a *Cocycle* if the dual produces a simple cycle



For a arbitrary (fixed) path  $P$  in  $G$ .

$$\pi(e) := \begin{cases} 1 & e \in P \\ -1 & e \notin P \\ 0 & \text{otherwise} \end{cases}$$

For a cycle  $C$  in dual, this counts the number of left to right crosses minus the number of right to left crosses.

$\pi(C) \in \{-1, 0, 1\}$  for any cocycle  $C$  and  $\pi(C) = 1 \iff C$  is a  $(s, t)$ -cut.

For a arbitrary (fixed) path  $P$  in  $G$ .

$$\pi(e) := \begin{cases} 1 & e \in P \\ -1 & e \notin P \\ 0 & \text{otherwise} \end{cases}$$

For a cycle  $C$  in dual, this counts the number of left to right crosses minus the number of right to left crosses.

$\pi(C) \in \{-1, 0, 1\}$  for any cocycle  $C$  and  $\pi(C) = 1 \iff C$  is a  $(s, t)$ -cut. Apply Jordan curve, and do case analysis on side location of  $t, s$ . Cycle is polygon.

For  $\lambda \in \mathbb{R}$  consider  $\lambda\pi$ .

Take the residual graph with  $c(\lambda, e) = c(e) - \lambda\pi(e)$ .

Flow is feasible  $\iff c(\lambda, e) \leq 0$ .

Consider the residual dual network  $c(\lambda, e^*) := c(\lambda, e)$ .

There exists a feasible  $(s, t)$  flow  $\iff$  the residual network  $G^*$  doesn't contain a negative cycle.

For  $\lambda \in \mathbb{R}$  consider  $\lambda\pi$ .

Take the residual graph with  $c(\lambda, e) = c(e) - \lambda\pi(e)$ .

Flow is feasible  $\iff c(\lambda, e) \leq 0$ .

Consider the residual dual network  $c(\lambda, e^*) := c(\lambda, e)$ .

There exists a feasible  $(s, t)$  flow  $\iff$  the residual network  $G^*$  doesn't contain a negative cycle. If there is a cycle:

$$c(\lambda, C^*) = \sum_{e \in C} c(\lambda, e) = \sum_{e \in C} c(e) - \lambda\pi(C) < 0$$

$\pi(C) = 1$  and  $C$  is a  $(s, t)$ -cut with a capacity smaller than  $\lambda$ .

# No negative cycles

Root a tree of SSSP at arbitrary  $o \in G_\lambda^*$

$$\phi(\lambda, e) = d(\lambda, \text{head}(e^*)) - d(\lambda, \text{tail}(e^*)) + \lambda\pi(e)$$

For an arbitrary  $v$ , the edges leaving  $v$  define directed (simple) cycle in  $G^*$  and the  $d$  cancels out  $\rightarrow$  the net value of sink is 0. This is a valid flow.

$\text{slack}(\lambda, e^*) := d(\lambda, \text{tail}(e^*)) - d(\lambda, \text{head}(e^*)) + c(\lambda, e) = c(e) - \phi(\lambda, e)$ , which is feasible by [4].



# No negative cycles

Root a tree of SSSP at arbitrary  $o \in G_\lambda^*$

$$\phi(\lambda, e) = d(\lambda, \text{head}(e^*)) - d(\lambda, \text{tail}(e^*)) + \lambda\pi(e)$$

For an arbitrary  $v$ , the edges leaving  $v$  define directed (simple) cycle in  $G^*$  and the  $d$  cancels out  $\rightarrow$  the net value of sink is 0. This is a valid flow.

$\text{slack}(\lambda, e^*) := d(\lambda, \text{tail}(e^*)) - d(\lambda, \text{head}(e^*)) + c(\lambda, e) = c(e) - \phi(\lambda, e)$ , which is feasible by [4].

Since path is arbitrary, for a fixed  $\lambda$  one can calculate the flow in  $O(n)$ .

Find the largest value  $\lambda$  that produces no negative cycles.

Find a  $\lambda$ , that induces a zero cycle. This is exactly the parametric shortest path problem.

WLOG: assume, that all the SSSP tree is always unique (standard perturbations, lexicographical...)

For  $\lambda \in [0, \lambda_{max}]$  a SSSP tree is well defined (and unique) except for some critical values.

For  $\lambda \in [0, \lambda_{max}]$  a SSSP tree is well defined (and unique) except for some critical values.

Edges of the tree point outwards, and  $slack(\lambda, p)$  (in dual) has exactly one incoming vertex.

For  $\lambda \in [0, \lambda_{max}]$  a SSSP tree is well defined (and unique) except for some critical values.

Edges of the tree point outwards, and  $slack(\lambda, p)$  (in dual) has exactly one incoming vertex.

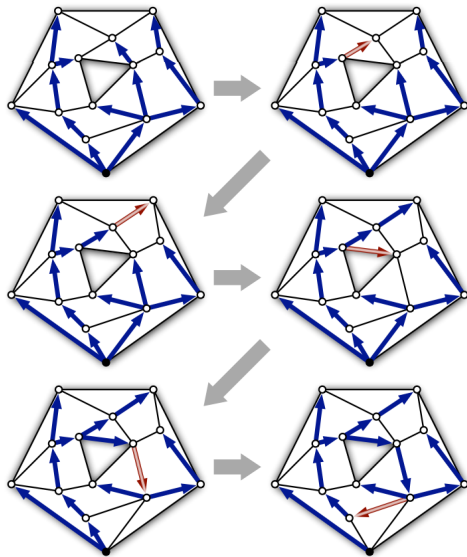
Of special interest are *tense* edges  $slack(\lambda, e^*) = 0$ , they always lie on the tree except on critical values of  $\lambda$  (pivots), where they get replaced by some other.

Loose edges in original graph are the ones where dual edges are not tense (spare capacity).

For  $\lambda \in [0, \lambda_{max}]$  a SSSP tree is well defined (and unique) except for some critical values.

Edges of the tree point outwards, and  $slack(\lambda, p)$  (in dual) has exactly one incoming vertex.

Of special interest are *tense* edges  $slack(\lambda, e^*) = 0$ , they always lie on the tree except on critical values of  $\lambda$  (pivots), where they get replaced by some other. Loose edges in original graph are the ones where dual edges are not tense (spare capacity).



Initialize the spanning tree of loose edges  $L_\lambda$ , SSSP predecessors for dual vertices and slack values for dual edges. This can be done in  $O(n \log n)$   
Crucial part is use of self adjusting top tree to efficiently update spanning tree in  $O(\log n)$  time.

Initialize the spanning tree of loose edges  $L_\lambda$ , SSSP predecessors for dual vertices and slack values for dual edges. This can be done in  $O(n \log n)$

Crucial part is use of self adjusting top tree to efficiently update spanning tree in  $O(\log n)$  time.

Final complexity:  $O(n \log n) + O(N \log n)$  where  $N$  is the number of pivot points.



Initialize the spanning tree of loose edges  $L_\lambda$ , SSSP predecessors for dual vertices and slack values for dual edges. This can be done in  $O(n \log n)$

Crucial part is use of self adjusting top tree to efficiently update spanning tree in  $O(\log n)$  time.

Final complexity:  $O(n \log n) + O(N \log n)$  where  $N$  is the number of pivot points. If  $t$  is incident to the outer face, each dual edge pivots in the shortest path at most once. (Borradaile proved  $O(n)$  pivots in general case).

Initialize the spanning tree of loose edges  $L_\lambda$ , SSSP predecessors for dual vertices and slack values for dual edges. This can be done in  $O(n \log n)$

Crucial part is use of self adjusting top tree to efficiently update spanning tree in  $O(\log n)$  time.

Final complexity:  $O(n \log n) + O(N \log n)$  where  $N$  is the number of pivot points. If  $t$  is incident to the outer face, each dual edge pivots in the shortest path at most once. (Borradaile proved  $O(n)$  pivots in general case).

Consider an infinite strip graph with two pivot paths with indices  $i < j$  Concatenate  $o_{-i} \rightarrow p_0$  and  $o_j \rightarrow p_0$  and loop.  $q_0$  is both in and out of the loop.

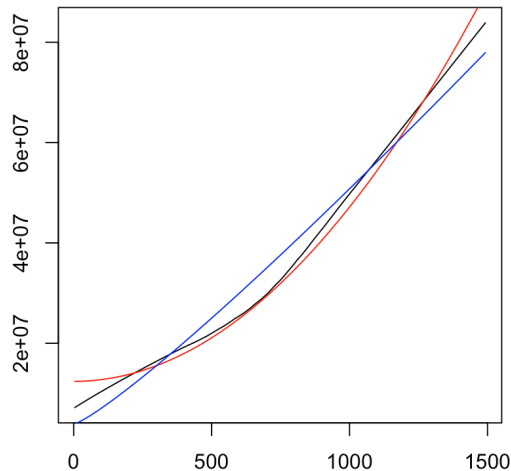
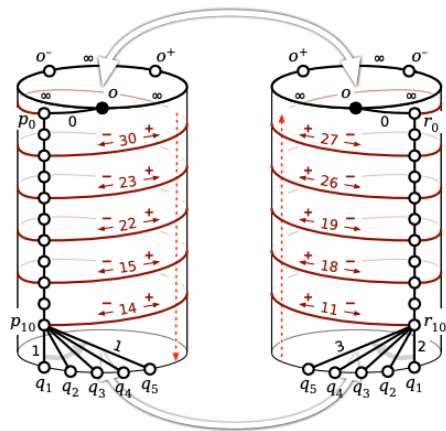
General algorithm given by [2] in  $O(g^7 n \log^2 n \log^2 C)$ .

In surfaces with higher genus, the decomposition of dual in  $L_\lambda$  is no longer (just) a tree, but might have additional edges.

Self adjusted trees can be modified to preserve the same time complexity.

The time complexity is still  $O(N \log n)$ , but  $N$  is  $O(n^2)$ .

# Dual $n^2$ case





BORRADAILE, G., AND KLEIN, P.

An  $o(n \log n)$  algorithm for maximum st-flow in a directed planar graph.

*J. ACM* 56, 2 (Apr. 2009).



CHAMBERS, E. W., ERICKSON, J., AND NAYYERI, A.

Homology flows, cohomology cuts.

*SIAM Journal on Computing* 41, 6 (2012), 1605–1634.



ERICKSON, J.

Maximum flows and parametric shortest paths in planar graphs.

In *Proceedings of the Twenty-First Annual ACM-SIAM Symposium on Discrete Algorithms* (USA, 2010), SODA '10, Society for Industrial and Applied Mathematics, p. 794–804.



FORD, L. R., AND FULKERSON, D. R.

Maximal flow through a network.

*Canadian Journal of Mathematics* 8 (1956), 399–404.



JOHNSON, D. B., AND VENKATESAN, S. M.

Partition of planar flow networks.

In *24th Annual Symposium on Foundations of Computer Science (sfcs 1983)* (1983), pp. 259–264.